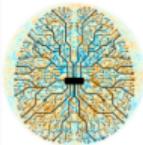


Machine Learning for Radiometer Calibration

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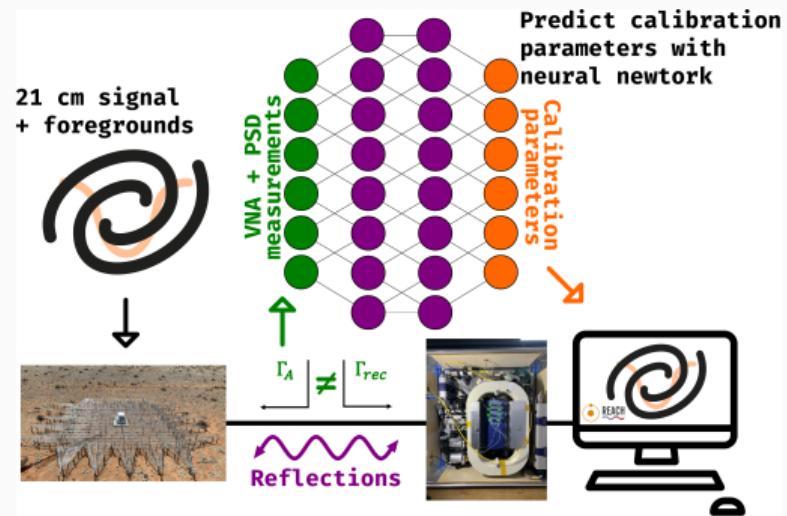
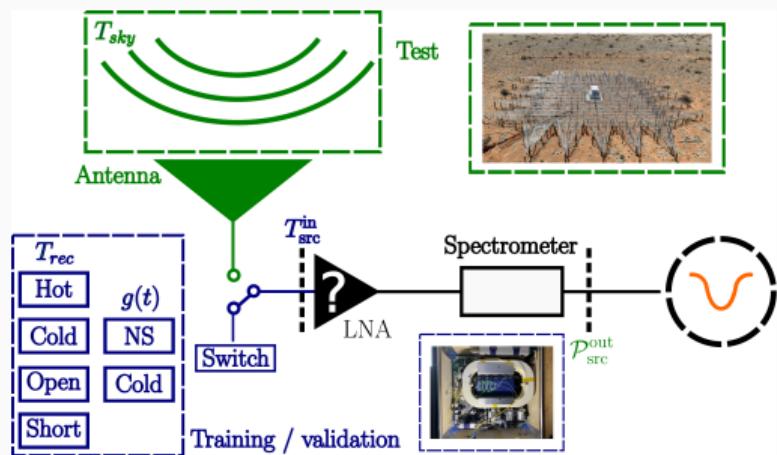
REACH



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ML calibration overview



Testing on internal validation source

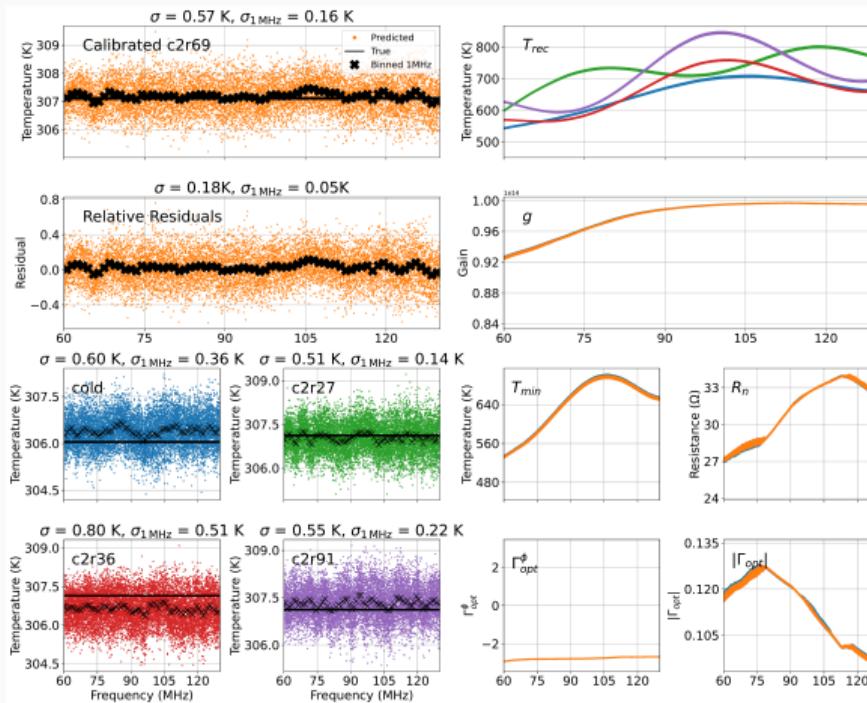
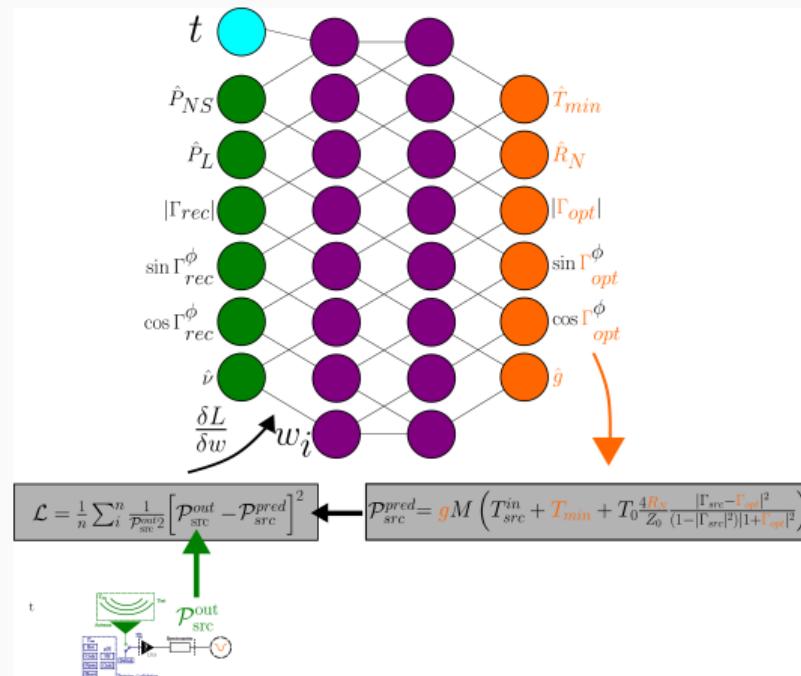
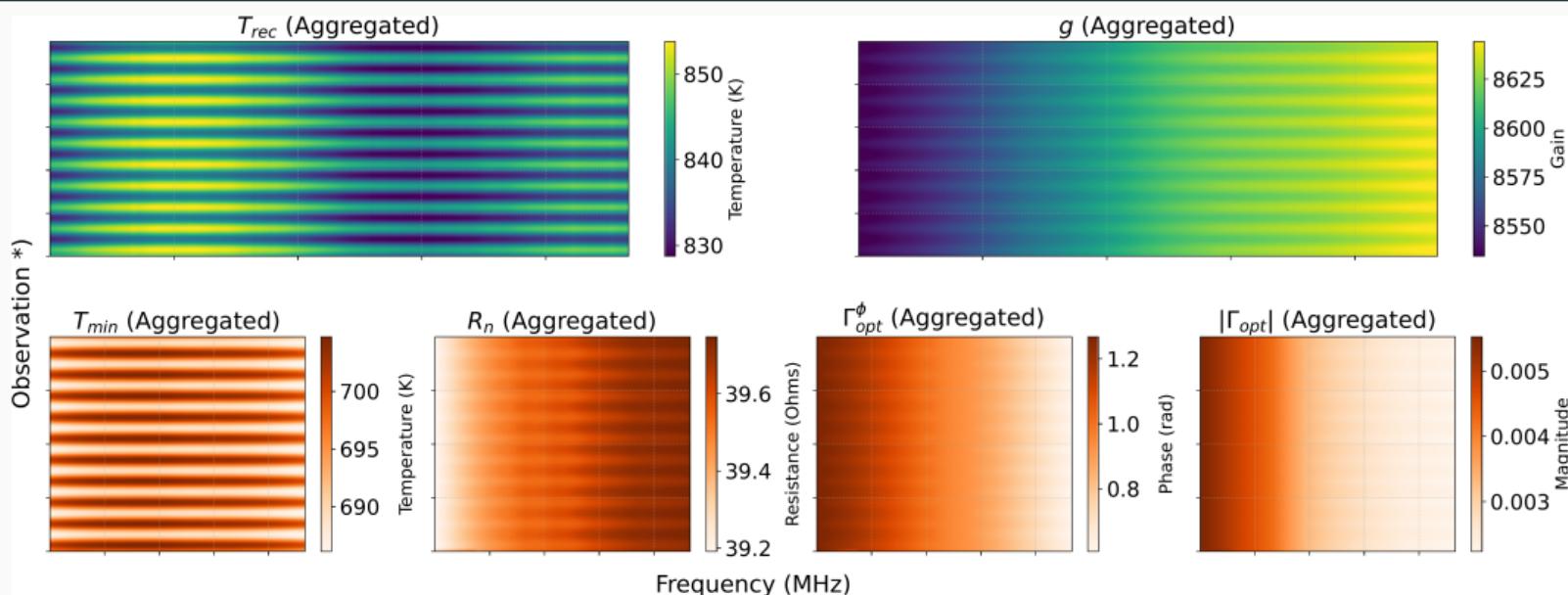


Figure 1: Temperature calibration using internal sources on the REACH receiver

Neural Network Time Evolution

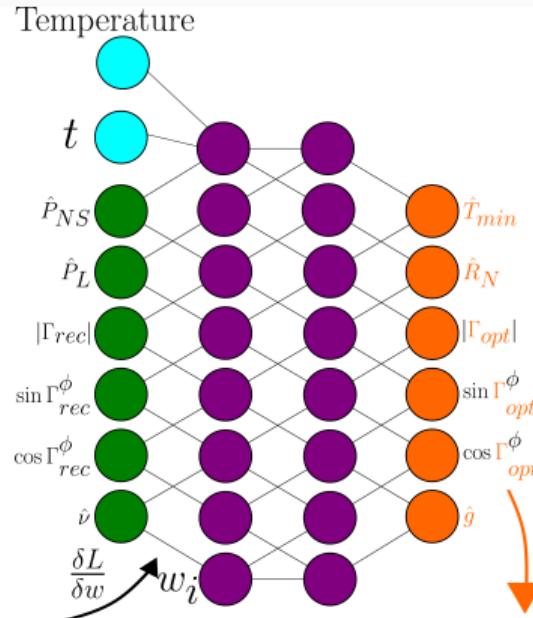


Inject system drift

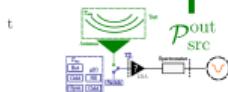


Inject a time varying sinusoid into T_{min} and predict the noise parameters → the network recovers this 'system drift'

Modeling environmental features



$$\mathcal{L} = \frac{1}{n} \sum_i^n \frac{1}{\mathcal{P}_{src}^{out2}} \left[\mathcal{P}_{src}^{out} - \mathcal{P}_{src}^{pred} \right]^2 \quad \leftarrow \quad \mathcal{P}_{src}^{pred} = gM \left(T_{src}^{in} + T_{min} + T_0 \frac{4R_N}{Z_0} \frac{|\Gamma_{src} - \Gamma_{opt}|^2}{(1 - |\Gamma_{src}|^2)(1 + |\Gamma_{opt}|^2)} \right)$$



We can train on features that cannot be modeled analytically

Conclusions

Component Modelling

Learn the effect of complex internal components such as switches, cables, etc

Temporal Dynamics

Learn time dependant system behaviour

Extended Inputs

Train on non-standard inputs, such as box temperature